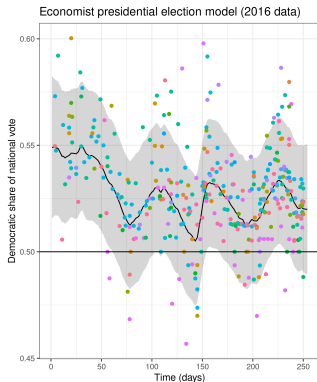


Approximate data deletion and replication with the Bayesian influence function

Ryan Giordano (rgiordano@berkeley.edu, UC Berkeley), Tamara Broderick (MIT)

Stanford Statistics Seminar May 2024

Economist 2016 Election Model [Gelman and Heidemanns, 2020]



A time series model to predict the 2016 US presidential election outcome from polling data.

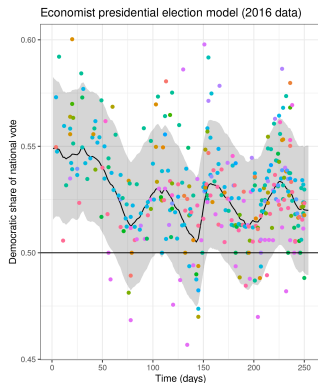
Model:

- $X = x_1, \dots, x_N =$ Polling data ($N = 361$).
- $\theta =$ Lots of random effects (day, pollster, etc.)
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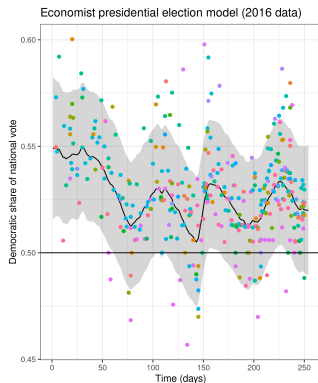
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If we had selected a different random sample, how much would our estimate have changed?

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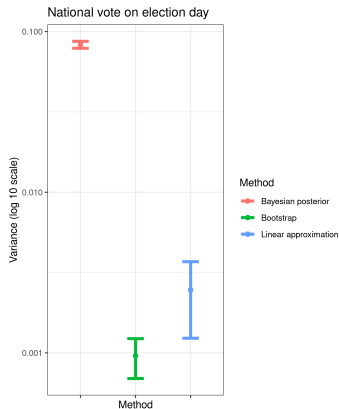
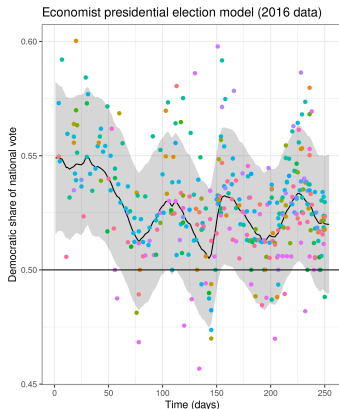
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Problem: Each MCMC run takes about 10 hours (Stan, six cores).

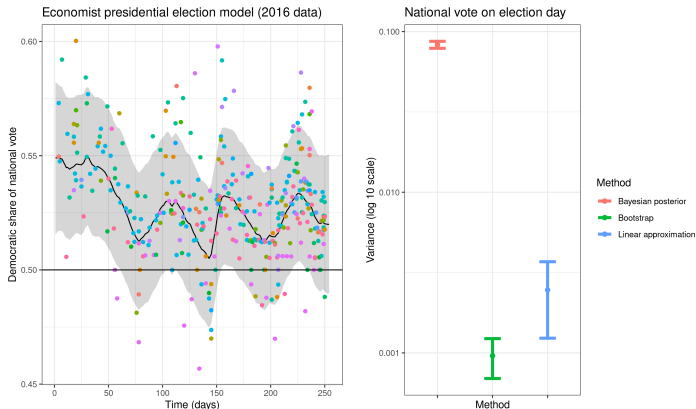
Results

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Compute time for 100 bootstraps: 51 days

Compute time for the linear approximation: Seconds
(But note the approximation has some error)

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- Some implications and future work

Data re-weighting.

Augment the problem with *data weights* w_1, \dots, w_N . We can write $\mathbb{E}_{p(\theta|X,w)}[f(\theta)]$.

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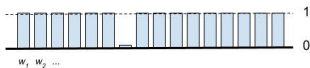
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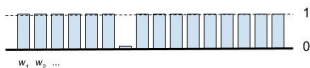
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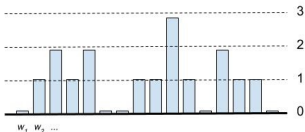
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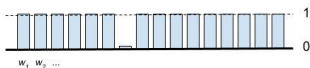
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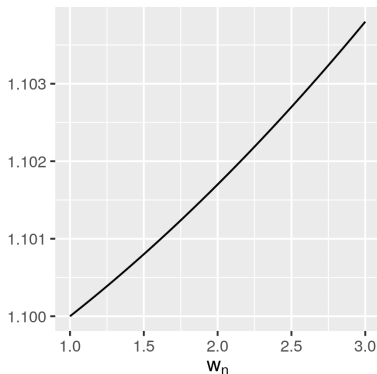
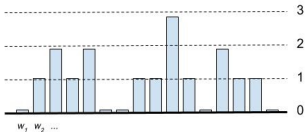
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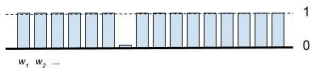
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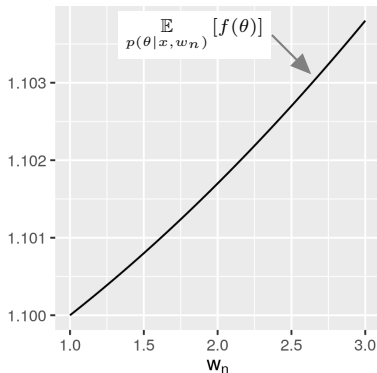
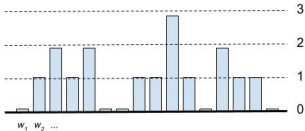
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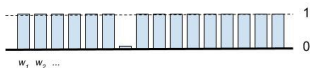
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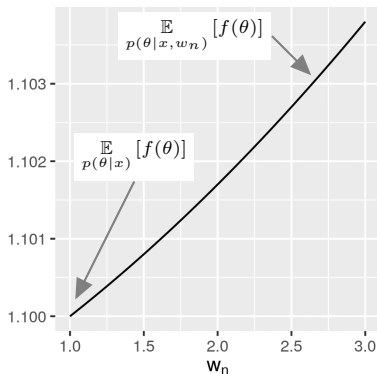
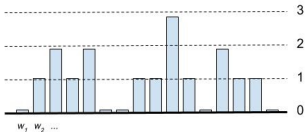
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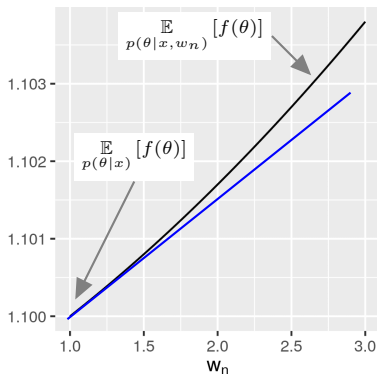
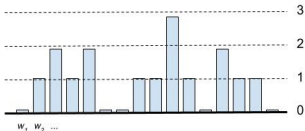
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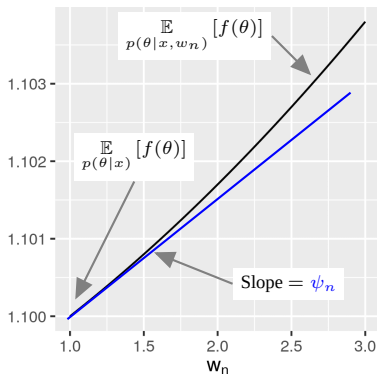
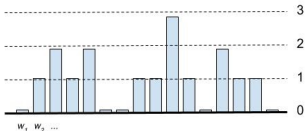
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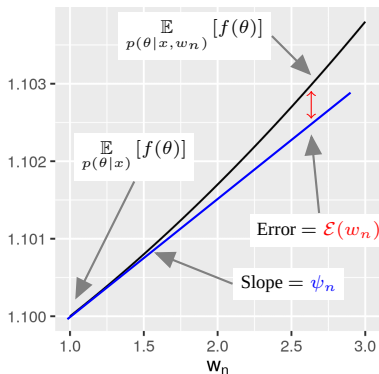
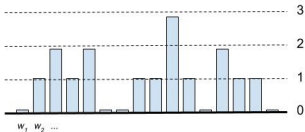
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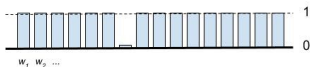
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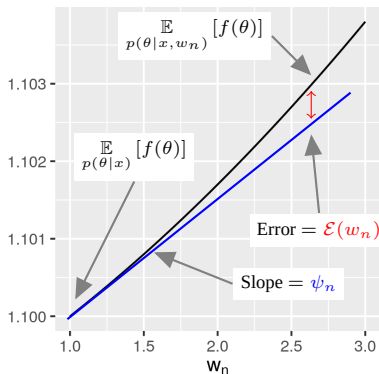
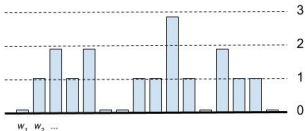
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The re-scaled slope $N\psi_n$ is known as the “influence function” at data point x_n .

$$\mathbb{E}_{p(\theta|X,w)}[f(\theta)] - \mathbb{E}_{p(\theta|X)}[f(\theta)] = \sum_{n=1}^N \psi_n(w_n - 1) + \mathcal{E}(w_n)$$

How can we use the approximation?

Assume the **slope** is computable and **error** is small.

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Expressions for the slope and error

How to compute the slopes ψ_n ? How large is the error $\mathcal{E}(w)$?

For simplicity, let us consider a single weight for the moment.

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Let an overbar denote “posterior–mean zero.” For example, $\bar{f}(\theta) := f(\theta) - \mathbb{E}_{p(\theta|X)} [f(\theta)]$.

By dominated convergence and the mean value theorem, for some $\tilde{w}_n \in [0, w_n]$:

$$\psi_n = \underbrace{\mathbb{E}_{p(\theta|X)} [\bar{f}(\theta) \bar{\ell}_n(\theta)]}_{\text{Estimatable with MCMC!}} \quad \mathcal{E}(w_n) = \frac{1}{2} \underbrace{\mathbb{E}_{p(\theta|X, \tilde{w}_n)} [\bar{f}(\theta) \bar{\ell}_n(\theta) \bar{\ell}_n(\theta)]}_{\text{Cannot compute directly (don't know } \tilde{w})} (w_n - 1)^2$$

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Theorem 1 [Giordano and Broderick, 2023] (paraphrase):

If the posterior $p(\theta|X)$ “concentrates” (e.g. as in the Bernstein–von Mises theorem),^a then

$$w_n \mapsto N \left(\mathbb{E}_{p(\theta|X, w_n)} [f(\theta)] - \mathbb{E}_{p(\theta|X)} [f(\theta)] \right)$$

becomes linear as $N \rightarrow \infty$, with slope $\lim_{N \rightarrow \infty} \psi_n$.

^aExisting results are sufficient for a *particular weight* [Kass et al., 1990]. Giordano and Broderick [2023] proves that the result holds when averaged over all weights, as needed for variance estimation.

Negative binomial experiment

Example: Negative binomial models with an unknown parameter γ .

For $n = 1, \dots, N$ let $x_n | \gamma \stackrel{iid}{\sim} \text{NegativeBinomial}(\alpha, \gamma)$ for fixed α .

$$\text{Write } \log p(X | \lambda, \gamma, w) = \sum_{n=1}^N w_n \ell_n(\gamma).$$

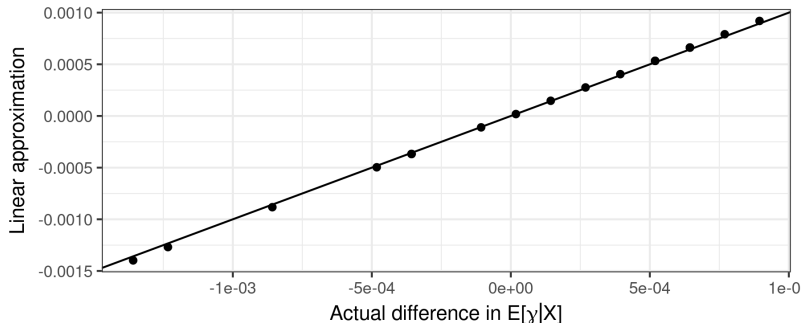
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Negative Binomial model
leaving out single datapoints with $N = 800$



Variance consistency theorem

How do the results for a single weight translate into variance estimates?

$$\text{Var}_{p(w)} \left(\mathbb{E}_{p(\theta|X,w)} [f(\theta)] \right) = \frac{1}{N^2} \sum_{n=1}^N \left(\psi_n - \bar{\psi} \right)^2 + \text{Term involving } \mathcal{E}(w_n) \text{ for } n = 1, \dots, N$$

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- Assume: A well-behaved MAP *maximum a posteriori* estimator $\hat{\theta}$ exists.
 - The dimension of θ is fixed as $N \rightarrow \infty$.
 - The expected log likelihood has a unique maximum at θ_∞
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 - The expected log likelihood Hessian \mathcal{I} is negative definite at θ_∞
- Assume: We can apply standard asymptotics.
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Theorem 2 [Giordano and Broderick, 2023]: Under the above assumptions,

$$\sqrt{N} \left(\mathbb{E}_{p(\theta|X)} [g(\theta)] - g(\theta_\infty) \right) \xrightarrow[N \rightarrow \infty]{dist} \mathcal{N}(0, V^g) \quad \text{and} \quad [\text{Kleijn and Van der Vaart, 2012}]$$

$$V^{\text{IJ}} := \frac{1}{N} \sum_{n=1}^N \left(\psi_n - \bar{\psi} \right)^2 \xrightarrow[N \rightarrow \infty]{prob} V^g. \quad (\text{our contribution})$$

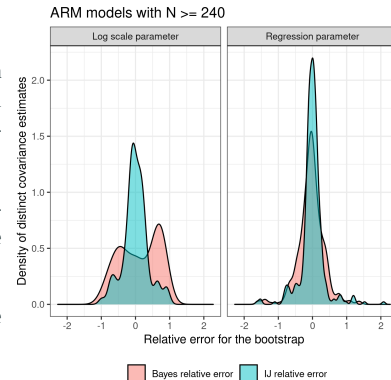
Data Analysis Using Regression and Multilevel/Hierarchical Models.

We ran `rstanarm` on 56 different models on 13 different datasets from Gelman and Hill [2006], including Gaussian and logistic regression, fixed and mixed-effects models.

Across all models, we estimate 799 distinct covariances (regression coefficients and log scale parameters).

Using the bootstrap as ground truth, compute the relative errors:

$$\frac{V_{\text{Bayes}} - V_{\text{Boot}}}{|V_{\text{Boot}}|} \quad \text{and} \quad \frac{V_{\text{IJ}} - V_{\text{Boot}}}{|V_{\text{Boot}}|}.$$



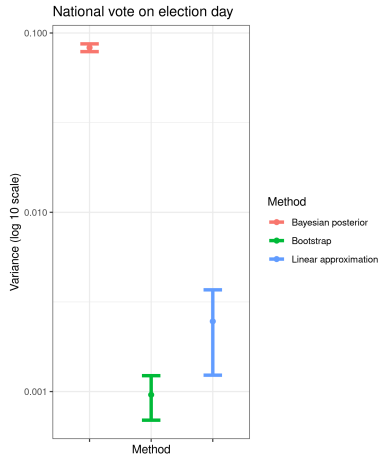
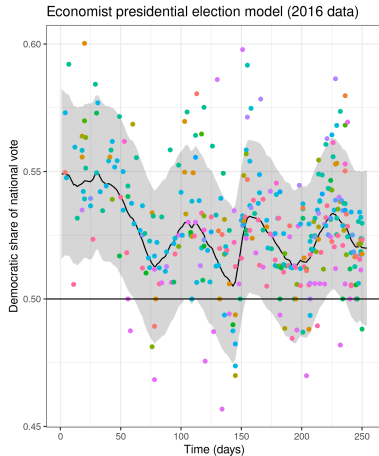
Total compute time for all models:

Initial fit: 1.6 hours

Bootstrap: 381.5 hours

How to connect to the election data?

Problem: MCMC is only interesting when the posterior doesn't concentrate.



Example: Exponential families with random effects (REs) λ and fixed effects γ .

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In general, we cannot hope for an asymptotic analysis of $\mathbb{E}_{p(\lambda, \gamma|X)} [f(\lambda)]$.

Can we save the approximation when *some* parameters concentrate?

Does the residual vanish asymptotically for $w_n \mapsto \mathbb{E}_{p(\gamma|X, w_n)} [\gamma]$?

High dimensional problems

We assume that $p(\gamma|X)$ concentrates but $p(\lambda|X)$ does not. By our series expansion:

$$\begin{aligned} \mathbb{E}_{p(\gamma, \lambda|X, w_n)}[\gamma] - \mathbb{E}_{p(\gamma, \lambda|X)}[\gamma] = \\ \psi_n(w_n - 1) + \mathcal{E}(w_n) \end{aligned}$$

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Corollary [Giordano and Broderick, 2023]:

In general, $w_n \mapsto N \left(\mathbb{E}_{p(\gamma|X, w_n)} [\gamma] - \mathbb{E}_{p(\gamma|X)} [\gamma] \right)$ remains non-linear as $N \rightarrow \infty$.

Example: Poisson regression with Gamma-distributed random effects

For $g = 1, \dots, G$, $\lambda_g \stackrel{iid}{\sim} \text{Gamma}(\alpha, \beta)$ for fixed α, β

For $n = 1, \dots, N$, $g_n \stackrel{iid}{\sim} \text{Categorical}(1, \dots, G)$, $y_n | \lambda_n, \gamma, g_n \stackrel{iid}{\sim} \text{Poisson}(\gamma \lambda_{g_n})$.

$x_n = (y_n, g_n)$ are IID given λ, γ . Write $\log p(X | \lambda, \gamma, w) = \sum_{n=1}^N w_n \ell_n(\lambda, \gamma)$.

Experiments

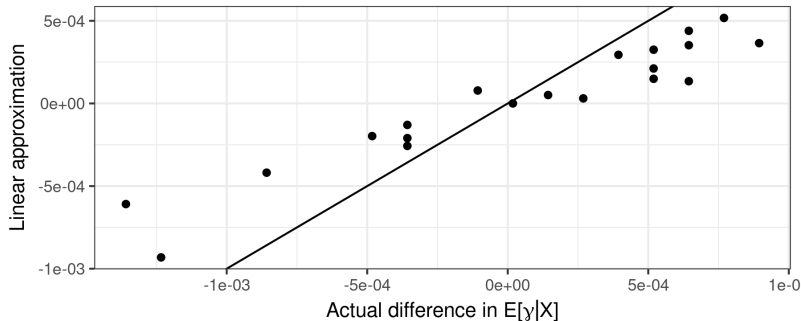
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Poisson random effect model
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Bayesian von-Mises Expansion

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Define the “generalized posterior” functional

$$T(\mathbb{G}, N) := \frac{\int g(\theta) \exp \left(N \int \ell(x_0 | \theta) \mathbb{G}(dx_0) \right) \pi(\theta) d\theta}{\int \exp \left(N \int \ell(x_0 | \theta) \mathbb{G}(dx_0) \right) \pi(\theta) d\theta}.$$

Let \mathbb{F}_N denote the empirical distribution. Then

$$\mathbb{E}_{p(\theta|X)} [g(\theta)] = \frac{\int g(\theta) \exp \left(N \frac{1}{N} \sum_{n=1}^N \ell(x_n | \theta) \right) \pi(\theta) d\theta}{\int \exp \left(N \frac{1}{N} \sum_{n=1}^N \ell(x_n | \theta) \right) \pi(\theta) d\theta} = T(\mathbb{F}_N, N).$$

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Let \mathbb{F} denote the true distribution of x_n , and let $\mathbb{F}_N^t = t\mathbb{F}_N + (1-t)\mathbb{F}$.

We can study the *von Mises expansion*:

$$\begin{aligned} \sqrt{N} \left(\mathbb{E}_{p(\theta|X)} [g(\theta)] - T(\mathbb{F}, N) \right) &= \sqrt{N} \left. \frac{\partial T(\mathbb{F}_N^t, N)}{\partial t} \right|_{t=0} (\mathbb{F}_N - \mathbb{F}) + \mathcal{E}(\tilde{t}) \\ &= \underbrace{\sqrt{N} \sum_{n=1}^N (\psi_n - \bar{\psi})}_{\text{Infinitesimal jackknife estimator}} + o_p(1) + \mathcal{E}(\tilde{t}). \end{aligned}$$

Theorem 3 [Giordano and Broderick, 2023] (sketch):

(Consistency of the von-Mises expansion in finite dimensions)

Under slightly stronger conditions our original finite-dimensional posterior consistency result,

$$\sup_{\tilde{t} \in [0,1]} |\mathcal{E}(\tilde{t})| \rightarrow 0 \quad \text{in the Bayesian von-Mises expansion.}$$

Bayesian von-Mises Expansion Results

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Theorem 4 [Giordano and Broderick, 2023] (sketch, not yet on arxiv):

(Inconsistency of the von-Mises expansion in infinite dimensions)

Assume that x_n comes with a random group assignment $g_n \in 1, \dots, G$. Conditional on g, x_n is modeled as a finite-dimensional exponential family given λ, γ :

$$\log p(x_n | g_n = g, \gamma, \lambda) = \tau(x_n)^\top \eta_g(\gamma, \lambda) + \text{Constant}.$$

Define the average product of second moments:

$$\mathcal{V}_{\mathcal{N}} := \frac{1}{N} \sum_{g=1}^G \mathbb{E}_{\mathbb{P}(x_n)} [\tau(x_n) \tau(x_n)^\top] \underset{p(\lambda, \gamma | \mathbb{F})}{\text{Cov}} (\eta_g(\gamma, \lambda)).$$

If $\mathcal{V}_{\mathcal{N}}$ is strictly bounded away from 0 as $N \rightarrow \infty$, then

$$\sup_{\tilde{t} \in [0,1]} |\mathcal{E}(\tilde{t})| \rightarrow \infty \quad \text{in the Bayesian von-Mises expansion.}$$

A contradiction?

Negative binomial observations.

Asymptotically linear in w .

Poisson observations with random effects.

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Is $\mathbb{E}_{p(\gamma|X,w)}[\gamma]$ linear in the **data weights** or not?

Trick question! We weight a log likelihood contribution, not a datapoint.

$$\log p(X|\gamma, w^m) = \sum_{n=1}^N w_n^m \log p(x_n|\gamma) \quad \log p(X|\gamma, \lambda, w^c) = \sum_{n=1}^N w_n^c \log p(x_n|\lambda, \gamma)$$

The two weightings are not equivalent in general.

What is the right exchangeable unit for a particular problem?

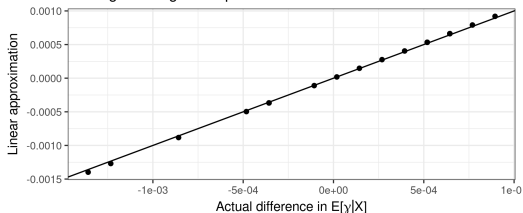
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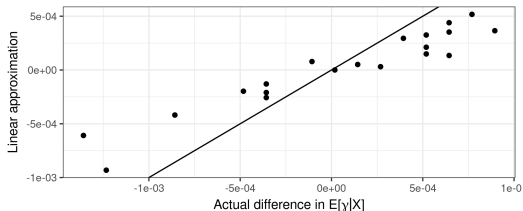
Negative Binomial model
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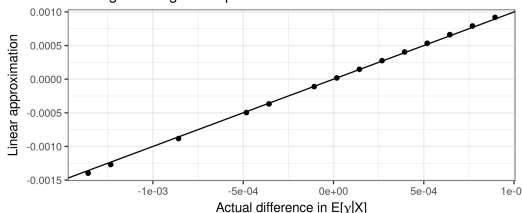
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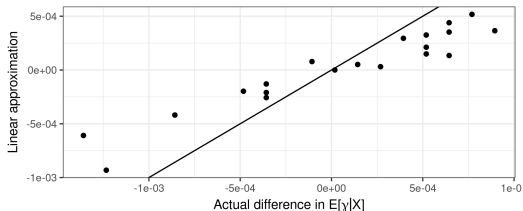
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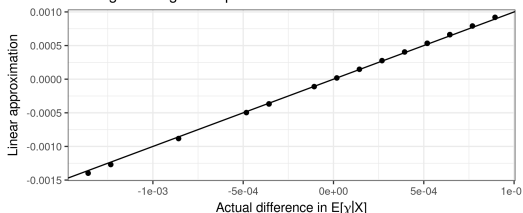
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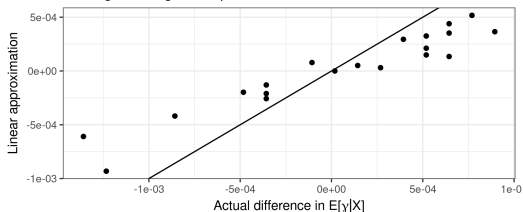
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May still be useful when $p(\lambda | X)$
is *somewhat* concentrated.

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Observations and consequences

- For finite-dimensional models which concentrate asymptotically:
 - Posterior expectations are approximately linear in data weights
 - The linearized variance estimate (infinitesimal jackknife) is consistent
 - The residual of the von Mises expansion vanishes
- For high-dimensional models which marginally concentrate only asymptotically:
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Preprint: Giordano and Broderick [2023] ([arXiv:2305.06466](https://arxiv.org/abs/2305.06466))

(Major update in progress, coming soon.)

- A. Gelman and M. Heidemanns. The Economist: Forecasting the US elections., 2020. URL <https://projects.economist.com/us-2020-forecast/president>. Data and model accessed Oct., 2020.
- A. Gelman and J. Hill. *Data analysis using regression and multilevel/hierarchical models*. Cambridge university press, 2006.
- R. Giordano and T. Broderick. The Bayesian infinitesimal jackknife for variance. *arXiv preprint arXiv:2305.06466*, 2023.
- J. Huggins and J. Miller. Reproducible model selection using bagged posteriors. *Bayesian Analysis*, 18(1):79–104, 2023.
- R. Kass, L. Tierney, and J. Kadane. The validity of posterior expansions based on Laplace’s method. *Bayesian and Likelihood Methods in Statistics and Econometrics*, 1990.
- B. Kleijn and A. Van der Vaart. The Bernstein-von-Mises theorem under misspecification. *Electronic Journal of Statistics*, 6: 354–381, 2012.

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Cross validation. Let $w_{(-n)}$ leave out point n , and loss $f(\theta) = -\ell(x_n|\theta)$.

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Example: Approximate bootstrap.

Draw bootstrap weights $w \sim p(w) = \text{Multinomial}(N, N^{-1})$.

$$\begin{aligned} \text{Bootstrap variance} &= \text{Var}_{p(w)} \left(\mathbb{E}_{p(\theta|x, w)} [f(\theta)] \right) \\ &\approx \text{Var}_{p(w)} \left(\mathbb{E}_{p(\theta|x)} [f(\theta)] + \psi_n(w_n - 1) \right) \\ &= \sum_{n=1}^N \left(\psi_n - \bar{\psi} \right)^2. \end{aligned}$$

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Influential subsets: Approximate maximum influence perturbation (AMIP).

Let $W_{(-K)}$ denote weights leaving out K points.

$$\max_{w \in W_{(-K)}} \left(\mathbb{E}_{p(\theta|x, w)} [f(\theta)] - \mathbb{E}_{p(\theta|x)} [f(\theta)] \right) \approx - \sum_{n=1}^K \psi_{(n)}.$$

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As $N \rightarrow \infty$, $p(\gamma|X)$ concentrates at rate $1/\sqrt{N}$ (Bernstein–von Mises).

$$\Rightarrow N \left(\mathbb{E}_{p(\gamma|X, w_n)} [\gamma] - \mathbb{E}_{p(\gamma|X)} [\gamma] \right) = \psi_n(w_n - 1) + O_p(N^{-1}).$$

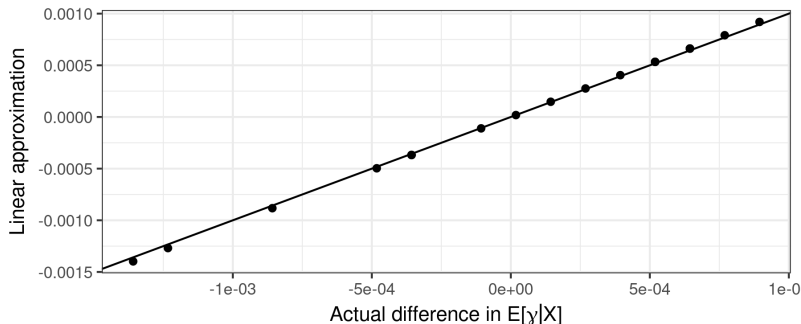
Example: A negative binomial model

Consider $p(X|\gamma) = \prod_{n=1}^N \text{NegativeBinomial}(x_n|\gamma)$. Here, $\theta = \gamma$ is a scalar.

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Negative Binomial model
leaving out single datapoints with $N = 800$



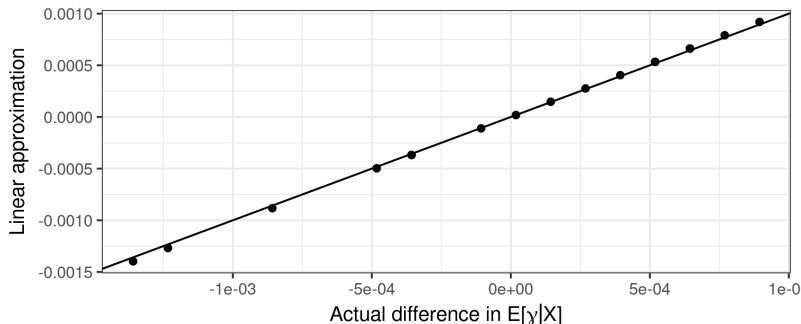
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Problem: Most computationally hard Bayesian problems don't concentrate.